Rainfall Triggered Landslide Early Warning System Based on Soil Water Index



H. G. C. P. Gamage, T. Wada, K. P. G. W. Senadeera, M. S. M. Aroos, and D. M. L. Bandara

Abstract Fourteen districts were identified as landslide prone in Sri Lanka. These districts fall in the wet and intermediate climatological zones where annual rainfall is over 2000 mm. Short term heavy rainfall and long term cumulative rainfalls are active factors for landslide occurrences. In this study, to enhance the landslide prediction capacity and accuracy, two indices were analyzed; Short Term Rainfall Index—1.5 h. half period Working Rainfall and Long-Term Rainfall Index—Soil Water Index. Also, regional critical Soil Water Index values were evaluated for the analysis of regional geological and other parametric impact on landslides. Hydrological Tank Model simulations were used to calculate Soil Water Index and to predict landslides with snake curves and probability curves. In regional aspect, tank model parametric analysis was carried in determination of suitable parameter set for each soil conditions. Rainfall intensity acts as the main contributing factor for Soil Water Index. With probability curves, better predictions were obtained on regional based soil water index of greater than 100 values to identify the landslide occurrences even though the Short-Term rainfall did not exceed 10 mm. Region-wise Critical Soil Water Indexes were obtained by critical lines with soil parameters derived for Sri Lankan soil conditions. Better practices on landslide early warnings could be performed through these derived regional long-term Soil Water indexes. As a future development, it is expected to develop warning levels based on these critical values.

1 Introduction

Quantifying the probability of landslide risk associated with heavy rainfall is necessary for a mountainous country (Shuin et al., 2014) like Sri Lanka to mitigate the damages for people and property due to landslide occurrences. Rainfall thresholds

H. G. C. P. Gamage · K. P. G. W. Senadeera (\boxtimes) · M. S. M. Aroos · D. M. L. Bandara Landslide Research and Risk Management Division, National Building Research Organisation, Colombo, Sri Lanka

[©] The Author(s), under exclusive license to Springer Nature Switzerland AG 2021 D. Amaratunga et al. (eds.), *Multi-Hazard Early Warning and Disaster Risks*, https://doi.org/10.1007/978-3-030-73003-1_36

for slope failures are essential information for establishing early-warning systems and for disaster risk reduction (Lin et al., 2020). National Building Research Organisation uses cumulative rainfall values for predicting landslide early warnings. 24 h cumulative rainfall is used for issuing landslide early warnings and categorizing them in to levels of risk: Watch for 75 mm and above, Alert for 100 mm and above, and Evacuation for 150 mm and above. These levels of risk were derived by previous researches. Rainfall affects for landside events in short term precipitation and long term precipitation. Later researches carried in finding the best long term and short term rainfall indices. As a resultant 1.5 h. half period working rainfall (1.5WR) and Soil water index were declared as the best short term rainfall index and the long term rainfall index respectively (Rajapaksha et al., 2019).

For enhancing the existing landslide early warning system, the concern was given on the soil water balance triggered by the rainfall in which represented by the soil water index (SWI). The objective of this study is to derive regional base critical SWI values as threshold values for issuing landside early warnings.

The Soil Water Index provides estimations on average amounts of water stored in the soil. Application of SWI helps to clarify the risk of landslide. Rainwater penetrates through the ground surface and discharges into the rivers or flows into the deeper ground. As the amount of water stored in soil increases, the risk of land slope collapse increases (Japan Meteorological Agency, 2018). Tank model which commonly used to estimate the relationship of rainfall and runoff is used for the SWI calculation. Tank Model is a conceptual model which simulates the moving behavior of water in the soil layers including runoff, infiltration and percolation (Hsu et al., 2018). Tank model used in this study consist of three tanks (Matlan et al., 2018) downward along the vertical soil profile namely: surface runoff, Intermediate and Ground water outflow (Fig. 1). At different levels of soil depths, different soil textures have various values of rates of discharges and infiltrations. In the tank model, each tank has a side outlet representing outflow to the surrounding soil and a bottom outlet representing outflow to deeper ground. Output from the side outlet of the first tank corresponds to surface runoff, that of the second tank corresponds to intermediate flow, and that of the third tank corresponds to base flow (Ground water outflow). Input to the first tank corresponds to rainfall, and input to the second and Third tanks is output from the bottom outlet of the upper tank (infiltration runoff) stored in soil of certain areas, helping to clarify the risk of landslide-related incidents caused by heavy rain (Japan Meteorological Agency, 2018).

The Japanese derived parameter sets including three parameter sets (Hsu et al., 2018) were used to study the regional characteristics of the moving behavior of the water. The three parameter sets were calibrated using mountainous small sub basins in Japan (Ishihara & Kobatake, 1979). One of the parameter set is utilized to evaluate landslide risks and practically applied to issue landslide early warnings by Japan Meteorological Agency and local governments. Therefore, applicability of the parameter sets for landslide warnings in Sri Lanka was evaluated in this study by validating the parameters based on Sri Lankan geological conditions. P1 is a moderate parameter set calibrated in Granite-dominant catchments. P2 parameter set



Fig. 1 Tank model

is for basins with gentle discharge increase and small discharge peak; P3 parameter set is for basins with rapid discharge increase and large discharge peak (Table 1).

1.1 Study Area

In Sri Lanka, 14 districts; Badulla, Ratnapura, Kandy, Nuwara Eliya, Kegalle, Kurunegala, Matale, Kalutara, Galle, Matara, Hambanthota, Moneragala, Colombo and Gampaha, have been identified for being prone to landside risk. Figure 2 shows the sub basins derived by using ArcGIS for the selected discharge gauging stations functioning under the Department of Irrigation. From this study area, it covers almost all the districts except Matale, Kurunegala, Colombo, Gampaha and Hambanthota. Few of the sub basins spread over two or more districts. Some of the sub basins consist of sub catchments (Table 2).

Table 1 Japanese parameters of the tank	k model													
Area type	L_1	L_2	L_3	L_4	\mathbf{S}_1	S_2	S_3	α1	α2	α3	α4	β1	β_2	β3
P1 (moderate peak, Granite)	09	15	15	15	0	20	30	0.15	0.1	0.05	0.01	0.12	0.05	0.01
P2 (gentle peak, Paleozoic)	75	30	5	15	0	20	30	0.15	0.1	0.05	0.01	0.12	0.04	0.01
P3 (sharp peak, tertiary and quaternary)	40	15	Ś	15	0	20	30	0.15	0.1	0.05	0.01	0.12	0.04	0.01

_
8
Ã.
Ξ.
÷
a
5
Ĕ
-
đ
Š
Ы
ž
e.
Ξ.
Ë
ä
5
š
B
a
đ
Ë,
-
e
ē
.



2 Materials and Methodology

2.1 Data Collection

Secondary data were used in the process of the analysis. The data collected for the analysis are tabulated in Table 3.

2.2 Process of Analysis

In the process of analysis, the flow of the tasks carried in this study mainly focused on developing the existing system of issuing landside early warnings focusing on SWI values which triggered by rainfall. Past data records of real time 30 min. rainfall data were collected for calculating 1.5 WR and the SWI for each catchment and sub basin. ArcGIS software was utilized for deriving sub basins and catchments of sub basins using Thiessen polygon and for the calculation of area of the sub basins which are

•				
Sub basin	Sub catchments	Bordering districts	River basin	Area (km ²)
Norwood	-	Nuwara Eliya, Ratnapura,	Kelani river	92.47
Deraniyagala	-	Kegalle	Kelani river	154.49
Holombuwa	-	Galle, Kalutara, Ratnapura, Matara	Gin gaga	Neluwa-171.891 Pallegama-190.727
Thawalama	Neluwa Pallegama	Matara, Ratnapura	Nilwala	Bengamuwa-13.59 Urubokka-35.83 Olampe-26.36
Urawa	Bengamuwa Urubokka Olampe	Moneragala Badulla	Kirindi	Wellawaya-95.62 Bandarawela-75.17
Wellawaya	Wellawaya Bandarawela	Moneragala Badulla	Kubukkan Oya	217.29
Nakkala	-	Nuwara Eliya Ratnapura	Mahaweli	182.46
Calidoniya	-	Kandy, Nuwara Eliya	Mahaweli	185.46
Nawalapitiya	-	Kandy, Nuwara Eliya	Mahaweli	185.46

 Table 2
 Study area; sub basins for the analysis

 Table 3
 Data used in the analysis

Task	Tank model parameters calibration and validation	SWI calculation (deriving critical lines and critical SWI values)
Data	Past 30 min. rainfall data records for derived sub basins and sub catchments from year 2016 to year 2019	Past 30 min. rainfall data records for derived sub basins and sub catchments from year 2014 to year 2020
	Observed hourly discharge data from year 2016 to year 2019	Past Landslide records from 2014 to 2020
	Other related data (geology, elevation, land use) maps	
	Tank model parameter data	

utilized on the tank model. When deriving catchments, the sub basin was divided into the number of sub partitions considering the consisting number of automated rain gauge stations within the sub basin.

A calibration process was carried out with a final validation process to certify the regional wise changes in tank model parameters. These confirmed, tested parameters were used for deriving the regional SWI critical values useful for issuing landside early-warnings. In testing the parameters, the patterns of the observed discharges and

calculated discharges were graphically compared and analyzed statistically. RMSE (Root Mean Square Error) and NSE (Nash–Sutcliffe model efficiency coefficient) (Vasconcellos et al., 2020) were used as the statistical analyzing methods. RMSE (Root Mean Square Error) is used to express how close the observed data points are to the model's predicted values. The Nash–Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the model's simulated variance compared to the measured data variance.

2.2.1 Calibration of the Tank Model Parameters

A developed macro program was used to analyze the hydro graphs of simulated and observed discharges in each basin to identify the best matching parameter-set.

Tank model parameters were calibrated with the observed and calculated discharges of the sub basins. In calculating the sub basin discharges, the average rainfall time series in the sub catchments were inputted to the tank model. Calculated discharges of the sub catchments were added together to obtain total discharges of the sub basins which consist of sub catchments.

The patterns of the simulated discharges and observed discharges were compared by plotting hydro graphs for the selected periods which had heavy rainfall.

The values of simulated and observed were statistically tested using RMSE and NSE for the selection of the identical parameter set which RMSE is closer to zero and NSE is closer to 1 (Vasconcellos et al., 2020).

2.2.2 Rainfall-Landslide Correlation Analysis Using SWI Calculations

A developed macro program was run to calculate SWI values and deriving critical lines and to define critical SWI values. The function of SWI was used to give an indication on the level of soil moisture in the area of landslide. The balance water quantity along the vertical soil profile was assumed as SWI value in the calculation. The outputs of SWI calculation were graphically represented via snake curves. The SWI equals to the total storage volume of three tanks laid vertically in series. The storage volume on each tank can be calculated using the following equations: (Sugawara, 1972).

$$\begin{split} &I_{1(t)} = \beta_1 \times \left(H_{1(t)} - (L_1 + L_2)_{(t)} \right); \ (I_1, \ I_2, \ I_3: \ Infiltration \ rates of \ Tank \ 1, \ Tank \ 2 \ and \ Tank \ 3) \\ &I_{2(t)} = \beta_2 \times \left(H_{2(t)} - L_{3(t)} \right) \\ &I_{3(t)} = \beta_3 \times \left(H_{3(t)} - L_{4(t)} \right) \\ &\Delta S_1 = R_{F(t)} - Q_{1(t)} + Q_{2(t)} - I_{1(t)}; \ (\Delta S_1, \ \Delta S_2, \ \Delta S_3: \ Water \ retention \ in \ Tank \ 1, \ Tank \ 2 \ and \ Tank \ 3) \\ &\Delta S_2 = I_{1(t)} - Q_{3(t)} - I_{2(t)} \\ &\Delta S_2 = I_{2(t)} - Q_{4(t)} - I_{3(t)} \\ &SWI = \Delta S_1 + \ \Delta S_2 + \ \Delta S_3. \end{split}$$

The calculated 1.5 WR and SWI time series and points of landslide occurrence were plotted together on snake curve charts to identify correlations between the landslide occurrence and triggering rainfall. Snake curve charts are scatter line charts consisting of short term rainfall index axis (Y axis) and long term rainfall index axis (X axis). Finally, CL was defined on a boundary of landslide occurrence and non-occurrence using Gaussian distributions.

3 Results and Discussion

3.1 Parameter Calibration and Validation

Based on the hydrographs as illustrated in Fig. 3a–e fittingness of parameter sets analyzed were tabulated in the Table 4. The regional parameter sets were certified depending on the RMSE values and NSE values. The parameter calibration was done by using the time series of the largest rainfall events from 2016 to 2019; moreover,



Fig. 3 Graphical representation of simulated discharges (Orange color) and observed discharges (blue color) with the real time observed rainfall (grey color)

Basin	District	Parameter sets obtained by calibration with major rainfall events		Parameter sets obtained by validation with minor rainfall events		Defined parameter set for each basin
		Parameter	NSE	Parameter	NSE	
Holombuwa	Kegalle	Р3	0.63	P1 P3	0.71 0.63	P3
Nawalapitiya	Kandy, Nuwara Eliya	Р3	0.60	Р3	0.30	Р3
Nakkala	Moneragala	Р3	0.85	P1 P3	0.44 0.40	P3
Wellawaya	Moneragala	P3	0.71	NA/(P1)	(-0.88)	P3
Deraniyagala	Kegalle	P1 P2 P3	0.61 0.66 0.56	P2 P3	0.29 0.35	P2
Norwood	Nuwara Eliya	P2	0.60	P2	0.32	P2
Thawalama	Galle, Kalutara, Rathnapura, Matara	P2	0.83	P2	0.28	P2
Urawa	Matara, Ratnapura	N/A(P2)	(-0.24)	N/A(P2)	(-0.69)	P2
Caildoniya	Nuwara Eliya	N/A (P1)	(-0.18)	P1	0.45	P1

Table 4 Analysis of tank model parameters

the parameter validation was done by using minor rainfall event data in 2019. The parameters in 7 basins of the total 9 basins showed reasonable reproducibility of the river discharge in the calibration periods (Table 4, NSE: 0.60–0.85). On the other hand, the NSE values in the validation periods were relatively low. It suggests that the tank model simulation is reasonable for major rainfall events in the calibration periods, but is relatively imprecise for minor rainfall events in the validation periods. The purpose of this analysis is to utilize the tank model for landslide early warnings. Therefore, accuracy during major rainfall events is critical for the purpose. NSE values of the 2 basins were negative even during major rainfall events in the calibration periods. However, it seems to be caused by overestimation of rainfall amount. Figure 3d, e shows the hydrographs of Urawa and Calidoniya in the calibration periods. The exceeding of simulated discharge was generated by the high observed rainfall. This observed rainfall values are assumed as overestimations, because total rainfall amounts were much higher than the amount of observed discharge. It seems that the rainfall gauging stations in the basins observed severe rainfall which occurred in a limited narrow area in a short period. Focusing on the increase and decrease rate of discharge except the peaks of rainfall, the trends of discharge increasing and decreasing have similar gradient in both simulated and observed discharge (Fig. 3d, e). Hence, it was concluded that the parameter sets of the tank model are reasonable to be applied for landslide early warnings during major rainfall events in Sri Lankan basin.

Hygrograph of discharges of Nawalapitiya basin (Fig. 3a) represents the characteristics of P3 parameter set. This parameter set create a sharp peak at a highest discharge. At the same time, hydrograph of discharges of Thawalama basin (Fig. 3b) represents the characteristics of P2 parameter set which give gentle peak discharges while the hydrograph of discharges of Caledonia basin (Fig. 3c) represents the characteristics of P1 parameter set which generate moderate peak discharges.

Figure 3a–e represent the time series hydrographs of discharges; *y axis Left- side discharge (cumecs), y-axis Right-side Rainfall (mm)*) at Nakkala Basin, Thawalama Basin, Calidoniya Basin *(calibrated results), Nakkala Basin and Calidoniya Basin (validated results).*

These parameters depend the on the geology, slope, land use, land cover and etc. In the analysis of geology in the sub basins, as an overall, the gneiss is the popular geology in the study area. With few differences, a similar geology distribution is seen in the respective basins. Therefore, the difference of tank model parameters in the basin is seemingly caused by other factors. The basins located in the southern area is the P2-gentle peak area; whereas, the basins in northern area is P3-sharp peak area. The mean slope in the P2 basins (15.4°) is steeper than P3 (13.7°) even though the discharge peaks in P3 are sharp. Thus, it seems that land cover and rainfall pattern affect the difference of runoff characteristics. Large amount and long period rainfall in the southwest slopes of Sri Lanka is usually caused by southwest monsoon. The rainfall causes dense forest and high infiltration; eventually, relatively gentle discharge peaks are seemingly generated in the southern area.

The clarified parameters mentioned above in Table 4 were used to calculate SWI and determine Critical Lines.

3.2 Rainfall-Landslide Correlation Analysis

The calculated 1.5 WR and SWI time series and points of landslide occurrence were plotted together on snake curve charts and time series charts to identify the rainfall-landslide correlation trigged by rainfall.

The calculated results of 1.5 WR, SWI, equal rainfall probability lines and disaster records at nine representative sub basins of river basins are shown on the snake curve charts of automated rainfall gauging stations within or closer to the derived sub basins operated by National Building Research Organization of Sri Lanka which are respectively located in the central hills, southeastern, northwestern, southern and southwestern sub-area of the study area. Calculated equal probability lines were also plotted together on the snake curve charts (Fig. 4).



Fig. 4 Regional critical Lines derived by probability curves Gaussian distribution and determined CSWI values *x* axis-SWI values *y* axis

Basin	Boundary districts	Probability of critical line using Gaussian Distribution (p value)	Critical SWI
Calidoniya	Nuwara Eliya, Ratnapura	0.005	132
Norwood	Nuwara Eliya, Ratnapura	0.04	117
Holombuwa	Kegalle	0.04	134
Deraniyagala	Kegalle	0.02	154
Nawalapitiya	Kandy, Nuwara Eliya	0.005	117
Nakkala	Badulla, Moneragala	0.04	114
Wellawaya	Badulla, Moneragala	0.005	101
Thawalama	Galle, Matara, Ratnapura, Kalutara	0.005	128
Urawa	Matara, Rathnapura	0.005	127

 Table 5
 Soil Water index values with probability lines determined by Gaussian distribution

As illustrated in Fig. 4a–i represent the SWI snake curve charts of Deraniyagala basin, Calidoniya basin, Holombuwa basin, Nakkala basin, Nawalapitiya basin, Norwood basin, Thawalama basin, Urawa basin and Wellawaya basin, respectively.

Critical lines (represent in blue dashed lines in Fig. 4.) were determined by selecting the probability lines on a boundary of landslide occurrence and non-occurrence using Gaussian distributions. For some basins, the critical line was determined on boundary of landside less occurrence and high frequent occurrence where the minimal occurrences take place below probability lines.

Table 5 shows the estimated critical value of SWI and p values of equal probability lines of estimated critical lines. The critical SWI ranged from 101 to 154. Even if the 1.5 WR is lower than 10 mm, the past landslides were caused by the high SWI condition. The equal probability line of 0.005 p value was determined as a critical line at 5 basins out of 9 basins.

Heavy rainfalls experienced at South West Monsoon (May–September) and North East Monsoon (December–February). Generally, in these periods, the heavy rainfall events continue for more than 10 days. Hence the cumulative rainfall is higher in the regions which affected by heavy rainfall, water retention in the soil increases and reaches to saturated level. After the saturation of soil water, the excess rainfall directly impacts on the slope stability. High values of SWI have a significant impact on destabilizing the slope. As an overall, the determined Critical Soil Water Indexes (CSWI) are above 100. Therefore, at a heavy rainfall event, if the SWI exceeds the limit of hundred, a certain landside occurrence risk could be expected in the landside prone regions.

4 Conclusion

Destabilization of slope depends on rainfall intensity, steepness of terrain and soil water content. Both the Short-term rainfall index (1.5 h. half period Working Rainfall) and the Long-term rainfall index (SWI) are useful for measuring the impact of short term and long-term rainfall intensities for the occurrence of landsides. Monsoonal activities directly impact on increasing the soil water storage due to the continuous heavy rainfall. A reasonable estimation of soil water amount could be obtained by SWI within the rainy season. The minimum regional threshold value of SWI for the occurrence of landslides is hundred. The range of regional SWI threshold values varies in between 100 and 160 for Sri Lankan soil texture for destabilizing the slopes. The threshold values of regional SWI can thus contribute to the development of effective early warning and evacuation system of Sri Lanka. In the periods of application, these findings revealed that the good prediction practices for landslide predictions for real cases taken place. It is expected to continue the collection of rainfall data and landslide records to improve early warnings by deriving warning levels based on these SWI values and evaluating SWI index values for predicting cutting failures which unstable the slope stability as future developments.

Acknowledgements This study is implemented as a part of JICA-Sri Lanka Project "Project for Capacity Strengthening on Development of Non-structural Measures for Landslide Risk Reduction in Sri Lanka". We appreciate the financial support from JICA's international and Government of Sri Lanka.

References

- Hsu, Y. K., Peng, S. H., & Tsai, C. W. (2018). Peak discharge and hydrograph assessments induced by heavy rainfall events using tank model. In *MATEC Web of Conferences* (Vol. 207, p. 02001). EDP Sciences.
- Ishihara, Y., & Kobatake, S. (1979). Runoff Model for Flood Forecasting.
- Japan Meteorological Agency. (2018). Soil Water Index, Runoff Index and Surface Water Index. https://www.jma.go.jp/jma/en/Activities/qmws_2018/Presentation/3.1/Soil%20Water% 20Index,%20Runoff%20Index,%20and%20Surface%20Water%20Index_revised.pdf
- Lin, G. W., Kuo, H. L., Chen, C. W., Wei, L. W., & Zhang, J. M. (2020). Using a tank model to determine hydro-meteorological thresholds for large-scale landslides in Taiwan. *Water*, 12(1), 253.
- Matlan, S. J., Abdullah, S., Alias, R., & Mukhlisin, M. (2018). Effect of working rainfall and soil water index on slope stability in Ranau, Sabah. *International Journal of Civil Engineering and Technology*, 9(7), 1331–1341.
- Rajapaksha, W. D. G. D. T., Wada. T., Jayathissa, H. A. G., & Priyankara, N. H. (2019). Determination of thresholds based on rainfall indices for the occurrence of landslides in Kalu Ganga basin, Sri Lanka. In 10th Annual Symposium, National Building Research Organisation
- Shuin, Y., Otsuka, I., Matsue, K., Aruga, K., Tasaka, T., & Hotta, N. (2014). Estimation of shallow landslides caused by heavy rainfall using two conceptual models. *International Journal of Erosion Control Engineering*, 7(3), 92–100.
- Sugawara, M. (1972). Rainfall-runoff analysis method. Tokyo: Kyoritsu Publishing (in Japanese).

Vasconcellos, S. M., Kobiyama, M., & de Almeida Mota, A. (2020). Evaluation of soil water index of distributed tank model in a small basin with field data. *Hydrology Earth System Science Discussions*. https://doi.org/https://doi.org/10.5194/hess-2019-682